

Intelligent Flight Control of Uninhabited Aerial Vehicles

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1 Introduction

This AASERT grant for the project entitled "Intelligent Flight Control of Uninhabited Aerial Vehicles" began 1 June 1997. This report is the Final Report for the period 1 June 1997 - 30 April 2000. The grant number of this project is F49620-97-1-0406. The parent award for this grant was F49620-95-1-0019. This grant ended 30 September 1997. The current parent grant is F49620-98-1-0037.

The principal investigator for this grant is Professor Dennis S. Bernstein. This grant supported the research of Dr. Tobin H. Van Pelt, who completed the Ph.D. degree in aerospace engineering at the University of Michigan in April 2000. Dr. Van Pelt is a U.S. citizen.

The goal of this project was to develop, implement, and demonstrate intelligent flight control technology. During the previous two reporting periods, construction of the flight test vehicle Solus² was completed and flight tests were conducted validating various aircraft systems. The paper [1] describes Solus² and its research objectives. Financial support for the hardware development of this vehicle was provided by the University of Michigan.

Theoretical research under this grant focused on developing identification methods that were suitable for on-line implementation. The most recent research reported in [2] concerns the development of a new linear identification method. This research improves standard least squares estimates by applying a quadratic constraint on the system transfer function coefficients. This work is being prepared for submission to IEEE Transactions on Automatic Control. Previous research in [2] and [3] developed nonlinear identification methods. These methods are least squares based and identify block-structured systems that contain static nonlinearities and dynamic linear blocks, and can be implemented on-line. The work in [2] and [3] has been submitted to the International Journal of Control. Furthermore, previous research in [4] considered linear identification methods that used sparse over-parameterizations. This research is closely related to adaptive control methods developed under the parent grant [5] and [6].

2 Identification

Empirical or data-based modeling, generally referred to as system identification, plays an essential role in control systems engineering as well as many other branches of science and engineering. While advances in robust and adaptive control methods for linear and nonlinear systems have helped to decrease reliance on plant models, the fact remains that models continue to play an important role in controller synthesis. Analytical models are essential for plant and control architecture design prior to plant fabrication, but these models contain assumptions that may be very difficult or impossible to verify. Consequently, such models are rarely accurate enough to provide precise prediction of the plant behavior for tuning high performance controllers. On the other hand, models obtained from system identification methods incorporate the "real" system in a more direct manner through measured data, and thus reduce the dependence on modeling assumptions.

Another use for systems identification is within adaptive control. Adaptive control methods require an accurate model of the system in the presence of changing disturbances and when the system itself is varying due to anomalies such as sub-system failures, environmental changes, or system deterioration. On-line identification techniques provide models of the plant in real-time, and thus capture information about the changing system to be used by the adaptive controller.

One of the first challenges of system identification is the determination of a model structure. Linear models have been used extensively in control systems technology, but in practice, all real systems possess nonlinearities. Even when the plant dynamics can be well represented by linear models, it turns out that additional nonlinearities such as saturations and dead bands can be introduced by sensors, actuators and amplifiers, thus degrading the accuracy of the resulting linear model. Accordingly, both linear and nonlinear identification techniques are needed.

An additional challenge of system identification is the presence of disturbances that corrupt data obtained from an identification experiment. In practice, these disturbances could arise from sensor inaccuracies, actuator granularity or ambient process noise. Sometimes these disturbances are known and can be removed, but in general this is not the case. Whether or not these ambient disturbances can be removed during the identification experiment, it is clear that one of the primary challenges in system identification theory is the development of methods that are insensitive to noise-corrupted measurements. Additionally, when considering nonlinear systems it is increasingly more difficult to distinguish between the presence of noise-corrupted measurements and actual nonlinear phenomena.

One of the most commonly used identification techniques is the prediction error method with a quadratic cost function. When the model structure to be identified is linear in parameters, this technique leads to a linear least squares problem which has an analytic solution that is easily implementable. Our research has focused on identifying linear and nonlinear model structures that can be identified using a least squares cost. Moreover, we have extended the standard least squares theory by incorporating quadratic constraints. The motivation for using least squares methods is that these methods have closed form solutions, are easily implemented on-line, and continue to be one of the most commonly used mathematical tools in all of engineering.

3 Linear Identification

Least squares is a widely studied technique for data analysis and system identification, and it has application throughout applied mathematics and engineering. A critical issue associated with least squares identification is the effect of noise on the parameter estimates. A desirable property of any system identification procedure is that the estimates be consistent, that is, the parameter estimate converges with probability one to the true parameter as the number of data points increases. In the case of least squares it is well known that the parameter estimates are not generally consistent. However, consistency is achieved when the residual error is uncorrelated. Two specific cases in which this occurs are the case of white equation error and the case of a finite impulse response (FIR) model structure.

The case of white equation error is a highly unrealistic situation. Alternatively, FIR models can be used within least squares. In this case all of the transfer function poles are constrained to be zero, which is clearly a non-valid assumption for infinite impulse response (IIR) systems. In addition, the numerator coefficients of a FIR transfer function are given by the impulse response, or Markov parameters of the system. Hence, it is interesting to note that the least squares estimates of the numerator coefficients are consistent estimates of the Markov parameters of the system even if the actual system is IIR.

There exist many variants of the least squares method that attempt to remedy the lack of consistency. Generalized least squares simultaneously builds a model of the system and the

noise, and is a special case of the prediction error method. Although generalized least squares is consistent when using this method, the least squares cost is nonquadratic in the parameters and requires numerical optimization procedures. In addition, consistency is guaranteed only for the global minimizer which may be difficult to obtain numerically.

Another extension of least squares identification is the instrumental variable method, which uses constructed data sequences, known as instruments, that are uncorrelated with the noise. It has been shown that the instrumental variable method is generically consistent. However, for finite data, the accuracy of the instrumental variable method may be poor and in general, the choice of good instruments depends on the system and the noise in question.

When performing least squares identification, a specific parameterization of the system transfer function is assumed. In general, these parameterizations have an inherent ambiguity which results from the simultaneous scaling of the numerator and denominator polynomials of the transfer function. It is traditional to normalize the leading denominator coefficient of this transfer function to be unity ($a_0 = 1$). Virtually every treatment of least squares identification proceeds with the tacit assumption that this normalization entails no loss of generality with respect to least squares optimization. Moreover, the transfer function is generally assumed to be fully parameterized. The research in the next two sections loosens these assumptions on the system parameterization in order to reduce the effects of noise and obtain consistency.

3.1 Quadratically Constrained Least Squares

In this research we consider a more general parameter normalization for least squares identification. Specifically, instead of fixing a_0 , we enforce a quadratic parameter constraint on all of the system parameters. This approach admits the normalization $a_0 = \pm 1$ as a special case.

The least squares problem with a quadratic constraint was considered in [7]. This problem has the form

$$\min_x \|Ax - b\|_2 \quad \text{subject to} \quad \|Cx - d\|_2 = \alpha, \quad (1)$$

where $A \in \mathbb{R}^{m \times q}$, $x \in \mathbb{R}^q$, $C \in \mathbb{R}^{p \times q}$, $b \in \mathbb{R}^m$, $d \in \mathbb{R}^p$, and $\alpha > 0$. In the present research we consider the quadratically constrained least squares (QCLS) problem

$$\min_{\theta} \theta^T M \theta \quad \text{subject to} \quad \theta^T N \theta = \gamma, \quad (2)$$

where $M \in \mathbb{R}^{(2n+2) \times (2n+2)}$ is nonnegative definite, $N \in \mathbb{R}^{(2n+2) \times (2n+2)}$ is symmetric, $\theta \in \mathbb{R}^{2n+2}$, and $\gamma > 0$. In (2), θ represents the model parameter vector

$$\theta = [a_0 \quad \cdots \quad a_n \quad b_0 \quad \cdots \quad b_n]^T,$$

corresponding to the n th-order transfer function

$$G(\mathbf{q}^{-1}; \theta) = \frac{b_0 + b_1 \mathbf{q}^{-1} + \cdots + b_n \mathbf{q}^{-n}}{a_0 + a_1 \mathbf{q}^{-1} + \cdots + a_n \mathbf{q}^{-n}},$$

and $\theta^T M \theta$ is the square of the residual model error. Note that setting

$$N = \begin{bmatrix} \gamma & 0 & \cdots & 0 \\ 0 & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & \cdots & 0 \end{bmatrix}$$

is equivalent to enforcing the normalization $a_0 = \pm 1$. Thus, the QCLS problem specializes to the standard problem. It can be seen that (1) with $b = 0$ and $d = 0$ has the same form as (2) with $M = A^T A$ and $N = C^T C$. However, for the case of system identification, N may be indefinite, which is not allowed in the framework of [7].

In this research we show, rather surprisingly, that the parameter normalization $a_0 = 1$ entails a loss of generality with respect to least squares identification. Roughly speaking, parameter normalization (however invoked) and least squares optimization are not commutative operations; in fact, each choice of normalization (or quadratic constraint matrix N) potentially leads to a different minimizer of the least squares cost. Consequently, the normalization $a_0 = 1$ actually subverts parameter consistency except for the white equation error and FIR modeling cases mentioned above.

In the present research, for the case of finite data, we show that when a persistency condition is satisfied, there always exists a quadratic constraint matrix N such that (2) yields the true parameters of the system as a solution. However, the appropriate constraint matrix N depends on the noise realization and thus cannot be implemented in practice. Furthermore, when a persistency condition is satisfied, we show that there always exists a quadratic constraint matrix N , which depends on the noise statistics, such that the QCLS estimate is consistent. It turns out that, in the case of white equation error and FIR modeling, the appropriate constraint is equivalent to fixing a_0 . For practical implementation with finite data, we develop an iterative method for applying the technique that does not depend on knowledge of the noise statistics.

Numerical results demonstrate the improvement using QCLS identification. A 2nd order example was considered with colored noise resulting in a signal-to-noise ratio of 15, and a two-tone sinusoidal excitation input. Figure 1 shows the parameter estimate error for a typical run using standard least squares, an instrumental variable method, the QCLS method with known statistics and iterative QCLS. Both iterative QCLS and QCLS with known statistics exhibit less parameter error than standard least squares. Furthermore, the parameter estimate error of the iterative QCLS method is similar to that of the QCLS method with known statistics. Additionally, the frequency response of standard least squares, instrumental variables, and the iterative QCLS method, are shown in Figure 2. Again, the reduction in the parameter estimation error of the iterative QCLS method yields the most accurate model with respect to the frequency response of the system.

Method	$\ \Delta\theta_l\ _2$	Unstable Models (%)
LS	$2.35 \pm .0036$	0
IV	1.09 ± 2.19	37
QCLS	$.281 \pm .020$	2
N=Q	$.150 \pm .0068$	0

Table 1: Average parameter estimation error.

Table 1 shows the average $\Delta\theta_l$ plus or minus one standard deviation, over 100 runs considered, as well as the number of unstable models, for each method. The results show that the instrumental variable method is highly uncertain, and 37% of the identified models were unstable. Moreover, the standard least squares method produced models with large bias. In contrast, iterative QCLS produced models that had less bias than both the standard least squares and the instrumental variable methods. Additionally, only 2% of the models were unstable when

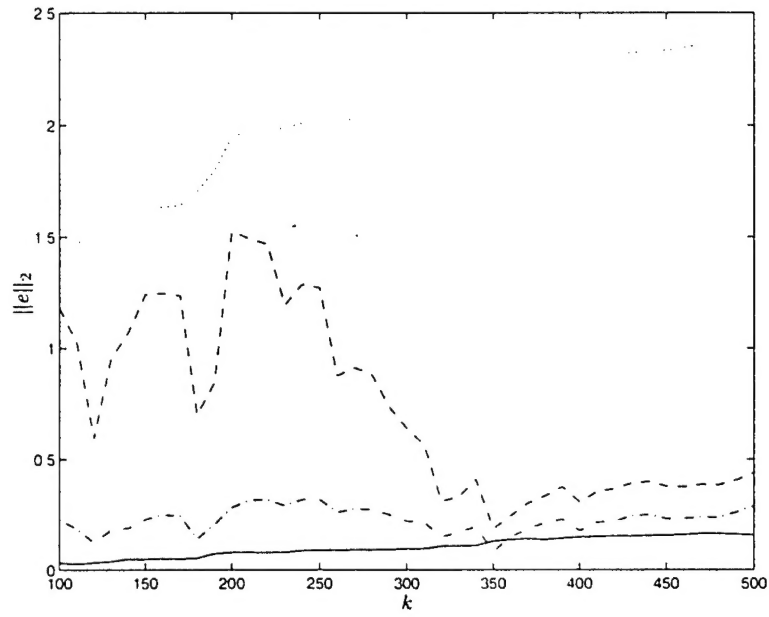


Figure 1: Parameter estimate error. (---- QCLS with known statistics ; — QCLS iterative method ; LS ; -.- IV)

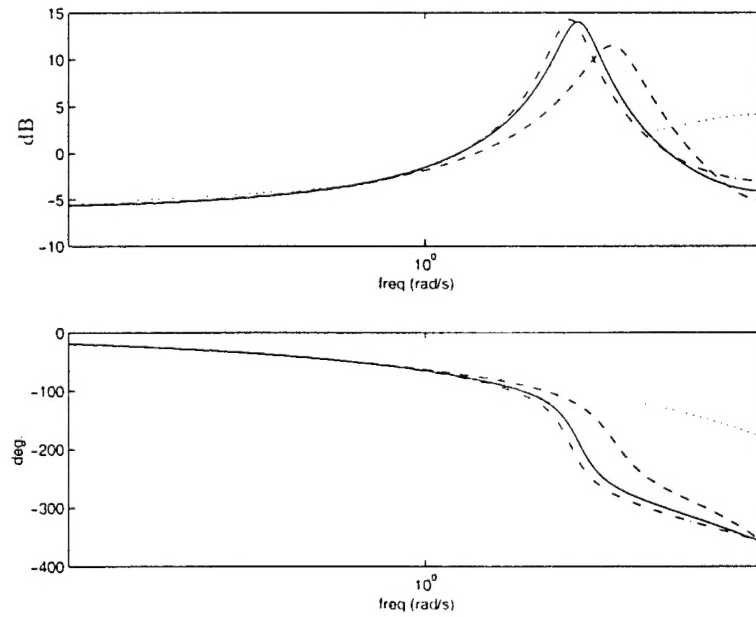


Figure 2: Frequency response of identified models at $k = 500$. (— True System ---- QCLS iterative method ; LS ; -.- IV)

using iterative QCLS.

3.2 μ -Markov Parameterizations

While a FIR model structure can be used to consistently estimate Markov parameters of a linear system, it turns out that convergence can be slow and more rapidly converging algorithms are of interest. One idea for improving the speed of convergence is suggested by the fact that the leading numerator coefficient of a fully parameterized transfer function is also a Markov parameter of the system. Therefore it is natural to seek model parameterizations whose numerator polynomials include an arbitrary number of Markov parameters without incorrectly constraining the pole locations of the model structure. The objective in using such models is to obtain consistent estimates of the system Markov parameters with a faster rate of convergence.

The significance of this result arises from the fact that the estimates of the Markov parameters can be extracted and used to construct a model of the system using realization theory. Since this procedure can be carried out whether the system is FIR or IIR, it can thus be seen that an “incorrect” model structure can effectively be used to construct a suitable identified linear model.

A suitable model structure that satisfies the above criterion is given by the class of step-ahead predictors, or equivalently, ARMARKOV (ARMA + Markov) models, which are non-minimal parameterizations, some of whose numerator polynomial coefficients coincide with Markov parameters. These models have been used extensively for adaptive control and identification [5-6].

Our previously reported research systematically developed and explored the properties of transfer function parameterizations that explicitly contain Markov parameters in the numerator polynomial. An interesting feature of these models is the relation between the number of Markov parameters appearing in the numerator and the sparse structure of the denominator polynomial. We characterized this relationship by defining μ -Markov parameterizations, which are non-minimal parameterizations of a transfer. The principal result of this research guarantees that when white noise excitation is used, the least squares estimates of the Markov parameters are consistent under a very general class of noise models, and regardless of model order choice. These Markov parameters can then be used with realization theory to obtain consistent model estimates. The significance of this result for obtaining consistent model estimates is that precise knowledge of the noise and the system order is no longer needed.

4 Nonlinear Identification

As previously reported, we have considered nonlinear identification using a model representation involving linear dynamic blocks (\mathcal{L}) and static nonlinear blocks (\mathcal{N}). These elements can be interconnected in various configurations, thus representing a large class of nonlinear systems. The most frequently used structures are the Hammerstein model ($\mathcal{N} \rightarrow \mathcal{L}$), the Wiener model ($\mathcal{L} \rightarrow \mathcal{N}$), and the nonlinear feedback model ($\mathcal{L} \rightarrow \mathcal{N} \rightarrow \mathcal{L}$), while other configurations are possible. Much of the previous work in nonlinear systems identification using this model structure has assumed that one or more of these subsystems are known a priori. Other work has relaxed this assumption while using iterative procedures.

In our research we develop a novel technique for nonlinear system identification using the

Hammerstein, nonlinear feedback, and Hammerstien/nonlinear feedback model structure. This technique simultaneously identifies the \mathcal{L} and \mathcal{N} blocks without a priori information of the system. The key to this research is the development of a parameterization of the nonlinear static maps that lead to a nonlinear least squares cost that can be reduced by means of an overbounding technique. This overbound entails a suboptimal, but computationally tractable, approximation to the original nonlinear least squares cost. In particular, this approach replaces the nonlinear least squares optimization problem with a pair of standard computational procedures, namely, linear least squares optimization and fixed rank approximation in the Frobenius norm.

This approach is based on a parameterization of the nonlinear static maps \mathcal{N} that is linear in parameters. Although there are many such parameterizations, piecewise linear functions are a prime candidate since they can approximate a large class of nonlinearities. These approximations have been widely studied in the circuit theory literature as well as in nonlinear control theory.

One of the challenges of this approach is in guaranteeing the invertibility of the regression matrix that arises in the linear least squares optimization problem. It is well known that the singularity of the regression matrix for problems involving a linear model structure is linked to persistency of excitation conditions on the input. A key feature of our method is the development of a "point-slope" representation for the parameterization of the approximating piecewise linear function. This parameterization guarantees the invertibility of the regression matrix. We have used this technique to develop nonlinear identification methods for Hammerstein, nonlinear feedback, and Hammerstein/nonlinear feedback model structures and we are currently working on Wiener and other more general configurations. Figure 3 shows an example of an identified nonlinear map corresponding to an input saturation. The use of this representation for the nonlinear static map \mathcal{N} is essential since using other representations such as standard interpolation result in singular regression matrices.

5 Status of Flight Experiments

The goal of the UAV program at the University of Michigan is to develop and demonstrate intelligent flight control techniques that are relevant to UAV applications and advance the state of the art in these areas. Specifically, the research and experimental focus of our project is in the fabrication of a testbed that is capable of performing on-line identification, fault detection and reconfiguration of flight controls. The expected result is a reduction in the risk and length of time associated with transitioning innovative research to flight control applications.

Our first aircraft was the UAV Solus. Solus was a $\frac{1}{4}$ scale Citabria with an embedded control system running a real-time operating system capable of communicating with a remote ground station during operation. During flight tests of Solus, many of our avionics and telemetry systems were tested. During these proof-of-concept flights it was discovered that the Citabria airframe was not ideal for our application due to weight and volume constraints and it was determined that a new airframe was needed.

Design and construction of a new aircraft began in January of 1998 and Solus² was completed in December of 1998. This new aircraft uses an upgraded embedded flight control system derived from Solus. Solus² utilizes a dual-boom, pusher configuration with a 5 h.p. two stroke engine. The aircraft weighs 55 lbs. and has a 131 in. wingspan. A photo showing the new aircraft is

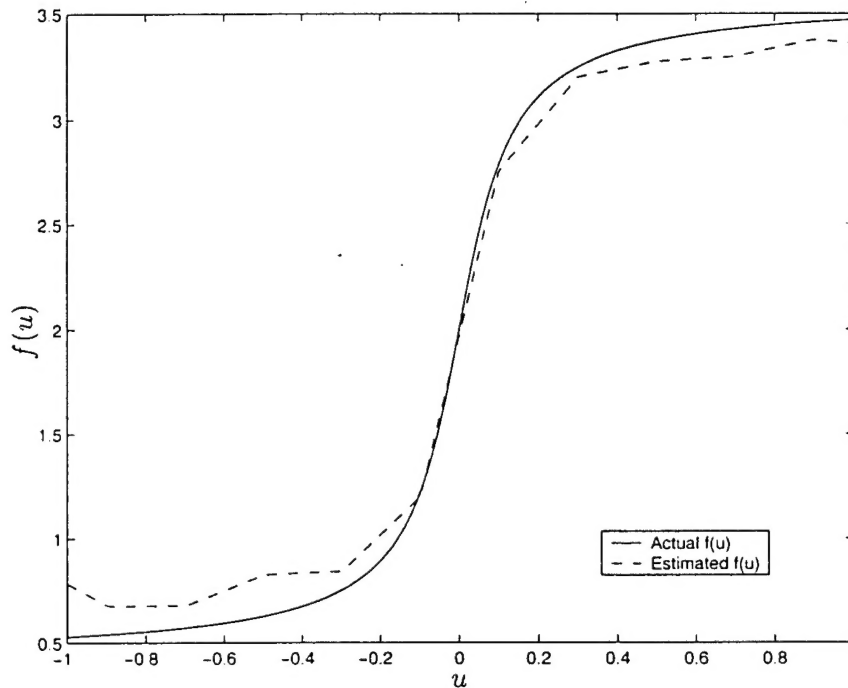


Figure 3: Estimate of a saturation nonlinearity in a Hammerstein system.

show in Figure 5.

Solus² carries an extensive package of sensors. It has an inertial measurement unit (IMU), an air data system (ADS), and a Trimble GPS receiver with an Accupoint Differential GPS correction unit. The design, construction, and calibration of the IMU and ADS were performed at the University of Michigan over the past year. Additionally, there is an engine tachometer to measure engine speed and potentiometers mounted on each control surface to measure control surface deflection.

The air data system measures the angle of attack, the angle of side-slip, and the dynamic pressure of the vehicle. The angles are sensed with vanes connected to potentiometers that align themselves with the local airflow, and the dynamic pressure is sensed with a Pitot probe that is connected to a pressure transducer. The resulting system is capable of providing the airspeed of the vehicle as well as the wind direction during flight.

The inertial measurement package consists of 6 Analog Devices solid state accelerometers, 3 British Aerospace solid state rate gyroscopes, and a Honeywell 3 axis solid state fluxgate magnetometer. Combined with the other sensor packages and appropriate filtering the complete state of the aircraft can be measured. The calibration was carried out at the University of Michigan using an Ideal Aeromath rate table and Singer Scorsby table.

The UAV can be controlled using two processors on the aircraft that communicate through dual ported RAM and are in contact with the instrumentation through a PC104 bus. Additionally, the aircraft is in contact with a ground station that consists of a single 120 MHz Pentium laptop. This ground station provides the user interface, data storage, and flight planning capabilities. The flight computer and ground station operate under the QNX real-time operating